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COMPUTER SELF-EFFICACY AND MATH PERFORMANCE IN ADULT BASIC EDUCATION STUDENTS

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COMPUTER SELF-EFFICACY AND MATH PERFORMANCE IN ADULT BASIC EDUCATION STUDENTS

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in Education
in the College of Education
at the University of Kentucky

By

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ABSTRACT OF THESIS

COMPUTER SELF-EFFICACY AND MATH PERFORMANCE IN ADULT BASIC EDUCATION STUDENTS

Domain-specific self-efficacy is increasingly known to be related to student academic performance. This study investigated the relationship between computer and math self-efficacy, math performance, and guided in-class use of an online educational program for adult basic education students enrolled in classes at an adult education program during the 2019 – 2020 school year. Initial math test scores and pre-survey results indicated no statistically significant relationship between computer self-efficacy and math performance, or math self-efficacy and math performance. After attending between 1 and 15 class sessions where an online educational program was used, post-survey results indicated no statistically significant relationship between guided in-class use of an online educational program and computer or math self-efficacy. Initial self-efficacy scores were found to have a negative and statistically significant relationship with changes in self-efficacy scores. These results suggest that further study is required and that students with very low self-efficacy may benefit the most from intervention strategies.

KEYWORDS: Computer Self-efficacy, Math Self-efficacy, Adult Basic Education, Adult Secondary Education, Computer-based Learning

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COMPUTER SELF-EFFICACY AND MATH PERFORMANCE IN ADULT BASIC EDUCATION STUDENTS

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DEDICATION

To my parents, Paul and Lynnette Dow,
who have worked so hard and given me so much.

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CHAPTER 1. INTRODUCTION

1.1 Background

Self-efficacy has emerged as a central part of social cognitive theory, and research on its effects on education and student performance are multitudinous (Bandura, 1986, 1997; Bandura & Locke, 2003; Pajares, 1996). As computer and technology use becomes increasingly more common in the classroom, on exams, and in the workplace, an understanding of computer self-efficacy can be a vital tool in serving students and employees (Compeau & Higgins, 1995; Moos & Azevedo, 2009). Computer-based testing in education is now the norm, and adult learners are no exception to this trend. Since the 1980's, instructors, researchers, and policy makers have been investigating the role of technology in the Adult Basic Education (ABE) and Adult Secondary Education (ASE) classroom (Johnson-Bailey, 2016; Kulik et al., 1986; Massoud, 1991; Rachal, 1993). While adult learners may seek to master the same content as traditional students in K-12 and postsecondary classes, adult learners have distinct needs and strengths, and ABE/ASE programs have their own distinct structure and resources to work with (Hernández-Gantes, 2010; Knowles et al., 2014; LeNoue et al., 2011; Safford-Ramus, 2008). Much of the literature on self-efficacy and student performance focuses on traditional students and adult students enrolled in vocational programs or other tertiary programs (Moos & Azevedo, 2009). But literature is sparser regarding a significant portion of the adult population in the United States.

Lack of a high school credential and low levels of literacy and numeracy affect millions of adults in the US. In 2019, approximately 27 million US adults 18 and over lacked a high school credential (United States Census Bureau, 2020). During the program year 2016, adult education programs, which include ABE, ASE, and ELL services funded through the Adult Education and Family Literacy Act, enrolled approximately 1.5 million individuals (Keenan & LeMaster, 2018). Kentucky has a population of approximately 4.5 million, with 12% of people aged 18 – 64 without a high school credential. During the 2014 – 2016 fiscal years, Kentucky Skills U, the state's adult education organization, enrolled 28,440 new GED-seeking students. A majority of these enrollees, 63%, fell within the ABE category (NRS Levels 1-4, or pre-literacy through approximately eighth grade level) (Kentucky Center for Statistics, 2019). Kentucky Skills U centers aim to help these students increase basic skills, attain a GED credential, and increase employability and college readiness.

The GED was most recently updated in 2014, and the release of the new GED exam has changed GED-attainment rates dramatically in Kentucky, as well as nationwide. In Kentucky, GED graduates dropped from 7,083 in the 2013-2014 program year to 1,663 in the 2014-2015 program year, a 76.5 percent decline (Briefing on Kentucky's Adult Education System, 2015). One of the potential barriers to completing the updated GED exam is the increased computer literacy required. In Kentucky, the only high school equivalency accepted is the GED credential, and the current GED exam is only available as a computer-based test. Basic computer skills, including a typing rate of at least twenty words per minute, are considered prerequisites to passing the GED exam, especially for short answer and extended response items (2014 GED Test Curriculum Blueprint from GED Academy, 2013). Additionally, the Test of Adult Basic Education (TABE), used for enrollment, progress-tracking, and reporting purposes, is administered primarily using the computer by KY Skills U programs. Computer literacy and digital media lessons are required by Kentucky Skills U (KYSU), but programs self-report their implementation of and success with these guidelines (Spalding, 2015). This means that data on computer literacy in the ABE/ASE classroom is difficult to obtain.

Computer access and literacy is often limited amongst the ABE/ASE population. Individuals lacking a high school credential have lower household income on average (Spalding, 2015), which may prevent regular access to technology. Approximately half of working age individuals in Kentucky without a high school credential are between the ages of 45 and 64 (Spalding, 2015), which means they may have had relatively low exposure to computers. Kentuckians without a high school credential are more likely to have health problems and disabilities (Spalding, 2015). These individuals may face further barriers to attending classes, and the classes themselves, along with the instructors, need additional resources to serve these students. ABE programs should consider carefully how they can best help their students build these necessary computer skills.

Self-efficacy is a strong determinant of academic performance, in that self-efficacy beliefs play a mediating role between factors such as cognitive ability, prior educational attainment and performance, and attitudes towards academics and academic performance. The link between domain-specific self-efficacy and academic performance is established in the research, including that math self-efficacy is a strong predictor of math performance (Bandura, 1997; Pajares, 1996). The relationship between computer self-efficacy and student persistence and performance with computer-based learning environments is less well-established (Moos & Azevedo, 2009). This may be partly due to their relatively recent introduction into academic settings, along with the proliferation of many different types and uses of computers in academic settings (Moos & Azevedo, 2009). Given that ABE and ASE students are required to perform on computer-based tests yet face many potential barriers to developing computer skills, alongside the fact that domain-specific self-efficacy is closely tied to academic performance, further investigation is required to understand the relationship between ABE/ASE student computer self-efficacy and math performance.

1.2 Research Questions

This study seeks to better understand the relationship between ABE/ASE student computer and math self-efficacy, computer-based instruction within a mathematics classroom context, and math performance on computer-based tests. Though computer self-efficacy is of primary interest in this study, math self-efficacy was included to provide a baseline of comparison with computer self-efficacy, as the connection between math self-efficacy and math performance is well-established in the literature (see Chapter 2). This study investigates the following research questions:

1. How do computer and math self-efficacy impact ABE/ASE student math performance on computer-based tests?
2. How does weekly, guided, in-class use of an online educational program affect ABE/ASE student computer and math self-efficacy?
3. How does weekly, guided, in-class use of an online educational program affect ABE/ASE student math performance?

CHAPTER 2. REVIEW OF THE LITERATURE

2.1 Introduction

The review of the literature presents an overview of self-efficacy, domain-specific self-efficacy, computer-based learning environments, and math performance as related to the ABE and ASE population. Going forward, ABE will be used to refer to both ABE and ASE. Many studies pertaining to self-efficacy, computer-based learning, and math performance focus on traditional K-12 students, college students, or adults in professional settings. Because of the relative dearth of literature on the specific population included in this study, the research included in this section provides a cross-section of studies on self-efficacy, computer-based learning, and math performance.

2.2 Social Cognitive Theory and Self-Efficacy

Self-efficacy is a foundational construct of social cognitive theory, a theoretical psychosocial framework developed by Albert Bandura (Bandura, 1986, 1997). Social cognitive theory is concerned with the agency of individuals and how personal beliefs and the exercise of control are used to shape their environment in a reciprocal relationship (Bandura, 1997). Bandura defines perceived self-efficacy as “beliefs in one’s capabilities to organize and execute the courses of action required to produce given attainments” (p. 3). Bandura uses the model of triadic reciprocal causation to understand the relationship between personal agency and other forces. Defining ‘causation’ as “functional dependence between events” (p. 5), this model posits that the relationships between behavior, internal personal factors (cognitive, affective, and biological events), and the external environment are reciprocal and causal in nature. That is, efficacy beliefs may be developed based on external factors, and efficacy beliefs cause action and the exercise of control over external factors (Bandura, 1997).

Sources of self-efficacy include mastery experience, modeling (vicarious experience), verbal (social) persuasion, and physiological reactions (Bandura, 1986, 1997). Mastery experiences are instances where an individual successfully accomplishes a given task, thus reinforcing the future belief in their ability to accomplish that task. Modeling gives an individual the opportunity to observe others accomplishing a given task, thus reinforcing the future belief in their own ability to accomplish that task – i.e., 'if they can do it, so can I.' Verbal, or social, persuasion from others can influence self-efficacy if it comes from a credible source – someone who is deemed knowledgeable about the given task. Persuasion must also be deemed realistic if it is to influence self-efficacy beliefs. Emotional and physiological reactions, such as anxiety, increased heartrate and sweating can also influence and individual's self-efficacy beliefs regarding a given task (Bandura, 1986, 1997; Bong & Skaalvik, 2003). Matsui, Matsui, and Onishi (1990) found that these four sources of math self-efficacy did make measurable contributions, yet they also showed the highly interrelated nature of the sources, such as with verbal persuasion and mastery experiences.

Because self-efficacy beliefs influence individuals' actions towards and performance on specific tasks, self-efficacy has greater explanatory power when understood at the appropriate level of specificity, rather than as a general measure (Pajares, 1996; Pajares & Miller, 1995; Bandura, 1997; Multon et al., 1991). Hackett (1985) describes math self-efficacy as beliefs about one's ability to perform well with regard to specific math tasks. Pajares and Miller's (1995) study of 391 university students found that math self-efficacy, as determined by being asked to judge their ability to solve specific math problems, was a stronger predictor of their actual performance in solving those math problems than either judgements about their ability to perform math-related tasks or succeed in math courses. Given the particularly task-oriented nature of self-efficacy, this may make the connection between self-efficacy and academic performance difficult to compare across a wide range of academic situations with varying student populations.

Similar to math self-efficacy, computer self-efficacy is the belief in one's own ability to use a computer to accomplish tasks (Compeau & Higgins, 1995). Students' computer self-efficacy has an influence on their choice of action, degree of effort, and persistence (Bandura, 1986). In their review of the literature, Moos and Azevedo (2009) found that relatively few studies have examined the relationship between computer self-efficacy and learning outcomes while using computers. Existing studies have focused on how computer self-efficacy is related to and changes over time with computer use and instruction. For example, Torkzadeh and Van Dyke (2002) found that attitudes towards computers are relatively stable by the time students reach adulthood, however computer self-efficacy can be modified through computer training programs (Torkzadeh & Koufteros, 1993). Moos and Azevedo found that in the existing experimental studies, it is quality of time spent learning with computers (including access to technical support and early mastery experiences with technical demands) over quantity or frequency that is a greater determinant of computer self-efficacy. Higher computer self-efficacy is associated with individuals being capable of adapting to and using computers in learning situations (Compeau & Higgins, 1995).

For students, self-efficacy's relationship to academic performance is well-established literature, despite its relatively short history (Pajares, 1996; Bandura & Locke, 2003; Bandura, 1997). Self-efficacy (or perceived self-efficacy), distinct from other concepts such as self-esteem and motivation, contributes independently to intellectual and academic performance, and is not simply a reflection of cognitive ability (Bandura, 1997). However, social cognitive theory recognizes that behaviors and performance result from a complex interplay of internal and external factors, of which self-efficacy is only one (Pajares, 1996; Bandura, 1997). Self-efficacy beliefs play a mediational role between diverse types of determinants (such as attitudes towards academic activities, prior education, gender, and self-esteem) and academic performance.

Constructs relating to value and outcome expectancies can also influence individuals' behaviors and performance (Schunk, 1989). Expectancy-value theories focus on how an individual sees that a particular outcome aligns with their values, and how likely that particular outcome is based on their expectations. For example, a student who values high grades may reasonably believe that studying contributes to high grades (Schunk, 1989). From the standpoint of self-efficacy, however, that student may not be motivated to actually study if they do not believe themselves to be capable of effectively studying and earning high grades. Self-efficacy theory focuses more on an individual's beliefs about their abilities to act in a certain way, rather than focusing directly on outcomes. A student who believes in their ability to study effectively, distinct from whether or not their studying pays off every time, might show greater persistence and motivation while working towards goals than a student whose beliefs about their abilities are more closely tied to the outcomes of their behaviors.

Self-efficacy can be difficult to disentangle from related concepts (Bandura, 1997; Pajares, 1996), such as self-concept. Self-efficacy is dependent on specific contexts as it focuses more on an individual's perceptions of their potential and skill, not on judgements of their abilities as compared to others. Self-efficacy pertains to an individual's belief in their ability to accomplish a specific task. Self-concept is the entirety of a person's perceptions of themselves. Self-concept is formed by experiences with the environment and is especially formed by experiences with others. Self-concept is heavily influenced by frames of reference, causal attributions, appraisals from others, mastery experiences, and psychological centrality (something perceived as important has greater influence) (Bong & Skaalvik, 2003). Both self-efficacy and self-concept have greater explanatory power when viewed through specific domains (Bong & Skaalvik, 2003; Bandura, 1997), rather than as general metrics. In their 2020 longitudinal study, Arens, Frenzel, & Goetz reviewed the literature on the relationship between math self-concept and math self-efficacy and found that some studies were inconclusive about the relationship (Jansen et al., 2015), but some found that self-concept influences self-efficacy over time (Bandalos et al., 1995; Ferla et al., 2009; Pajares & Miller, 1994; Randhawa et al., 1993; Seegers & Boekaerts, 1996). Their own analysis of data from 3,209 German secondary school students showed a positive relationship between former math self-concept and later math self-efficacy. That is, judgements about task-specific competence are partially influenced by their general self-perceptions regarding academic competence.

Academic anxiety, and especially math anxiety, is also strongly linked to math self-concept and math self-efficacy. Math anxiety is "tension and anxiety that interferes with the manipulation of numbers and the solving of mathematical problems in a wide variety of ordinary life and academic situations" (Richardson & Suinn, 1972, p. 551). As might be expected, research shows an inverse relationship between math anxiety and performance (Ashcraft & Krause, 2007; Jameson, 2013; Ma, 1999), and high math anxiety is correlated with low self-concept and self-efficacy (Meece, Wigfield, & Eccles, 1990; Lee, 2009). In a study of 226 undergraduate students, Jameson and Fusco (2014) found that non-traditional (adult) students had significantly lower levels of math self-efficacy compared to traditional students. However, they found that levels of math anxiety and self-concept were the same between groups. Given that low math self-efficacy is associated with low math self-concept and high anxiety elsewhere in the research, the authors posit that their results may be explained by the breakdown of their undergraduate students into traditional and non-traditional. Overall, they found that math self-efficacy levels were more sensitive to demographic shifts in the participants. As age of students increased, anxiety increased and self-efficacy decreased, and an inverse relationship was found between time since last math class and math self-efficacy. Further, self-efficacy was specifically low for the nontraditional students when it came to more 'academic' or abstract topics, such as geometry and trigonometry, whereas less of a difference was found when it came to more practical or fundamental topics such as fractions and decimals (Jameson & Fusco, 2014). Though this study focuses on adult students pursuing a college degree, the negative self-perceptions and attitudes found here and elsewhere in the research may be further extended to the ABE population, who may face even more barriers to developing positive self-perceptions and attitudes with regards to math and academic performance.

Self-efficacy beliefs are one determinant of academic performance. Research suggests that self-efficacy beliefs that are slightly higher than actual self-efficacy are beneficial to motivation and performance, and that strongly positive or strongly negative beliefs can have negative effects (Pajares, 1996; Bandura & Locke, 2003). Bandura and Locke (2003) found that perceived self-efficacy alongside personal goals strengthen motivation and performance. Self-efficacy has more predictive and explanatory power when measured at a level of specificity that matches related outcomes under investigation (Pajares, 1996). Academic performance is most often measured in one of two ways – grades and standardized test scores. In their 2020 longitudinal study of math self-concept and self-efficacy with respect to achievement, Arens, Frenzel, & Goetz found that, while academic self-concept was a stronger predictor of school grades, math self-efficacy was a stronger predictor of performance on math tests. Their results confirm previous work showing that self-efficacy is the stronger predictor when it comes to domain-specific test scores (Marsh et al. 2005; Ferla et al., 2009; Lee, 2009; Pajares & Miller, 1994).

For adults, a strong sense of self-efficacy is an important factor in determining the path that individuals construct for themselves. According to Bandura, "Those who enter adulthood poorly equipped with skills and plagued by nagging doubts about their capabilities find many aspects of their adult life aversive, full of hardships, and depressing (Bandura, 1997, p.184)." We may not think of adults as being as capable of altering and updating their beliefs and behaviors in accordance with their environment but exercising control over behaviors and environment is essential for adults in attaining and maintaining goals. In a study of 110 ABE students at two community colleges in rural and urban communities, Watts (2011) found a small negative correlation between age and math performance as measured by a standardized placement test, as well as age and math self-efficacy. The study found a strong significant correlation between math performance and math self-efficacy, and that self-efficacy level predict math performance more so than gender, age, or math anxiety.

2.3 Andragogy and the ABE Learner

Adult learners differ significantly from the child learner. Andragogy, or the theory of adult learning, came into focus in the 1970's with the work of Malcolm Knowles (Knowles, Holton, & Swanson, 2014). Knowles et al. (2014) outline a theory of andragogy guided by six key principles. First is the learner's need to know—adults address the questions of 'why,' 'what,' and 'how.' Second, the adult learner's self-concept is that of an autonomous and self-directing individual. Third is the prior experience of the learner—adult learners bring more prior experience, resources, and models of understanding to learning. Fourth, readiness to learn is impacted by the life relevance of a task. Fifth, adults' orientation to learning is problem-centered and context-specific. Finally, adults' motivation to learn may be driven by both the intrinsic value placed on knowledge, and the personal value to be gained from learning. This framework for understanding adult learners may be incomplete (Hernández-Gantes, 2010), especially in that it fails to address learning within context. ABE learners, especially within the context of the mathematics classroom, standardized test preparation, or online learning, may be lacking in the self-directing and self-regulating skills assumed in Knowles' framework.

Lenoue, Hall, & Eighmy (2011) summarize the framework of Knowles et al. as applied to the adult basic education (ABE) learner. Adults are motivated to learn by needs and interests arising in their everyday lives. Adults are autonomous and have a need to be self-directing in their education. However, ABE students may initially be lacking the self-regulation skills required in the context of mathematics education, online learning, and standardized test preparation. For these reasons, it is important that the ABE instructor take on the role of facilitator and partner in inquiry, rather than 'transmitter of knowledge.' Collaboration and interpersonal relationships have an important role in ABE. Adults are always learning and engage in many informal learning experiences in their everyday lives, outside of formal educational situations. Individual learning and knowledge differences amongst people increase with age, necessitating an educational program that addresses diverse skills and needs. Adults bring their life's worth of learning and experience to the ABE classroom (LeNoue et al., 2011). These aspects of adult learning and ABE can be used to inform curricula, learning environments, and content in ABE programs. The differentiated nature of ABE math learners with regards to prior knowledge and experience and self-regulatory skills becomes even more important in a free, open-enrollment adult education program.

The Adult Numeracy Network, an affiliate of the National Council of Teachers of Mathematics, outlines teaching and learning principles targeted at adult learners, and specifically ABE learners. While the NCTM and K-12 education focus on preparing children for all of the possible paths they might take in life, adult education is different (Safford-Ramus, 2008). As outlined above, adults, and particularly ABE learners, are driven by their personal goals and circumstances, and want to learn what they need to know. The Adult Numeracy Network guidelines for curriculum and learning environment state that the curriculum should "include opportunities for students to question, reason, solve problems, define goals and monitor their own progress by using estimation, mental math, computation, and technology when appropriate" (Adult Numeracy Network, 2005).

Autonomy, flexibility, and applicability are essential to the ABE math curriculum in order to best support adult learners in achieving their goals, and the guidelines specify that learners should be monitoring their progress and using technology where appropriate. These guidelines do not mention that most ABE learners are preparing for specific standardized tests which require the use of a computer. Viewed within that context, instructor-led opportunities for building technology skills and self-regulatory skills become central to the ABE curriculum.

2.4 Computer-based and online learning

Computer-based learning environments and definitions of online and computer-based learning vary widely within the research. This is likely due to the relatively recent development of this sector within education, and the huge proliferation of technology-based learning options. Moos and Azevedo (2009) define computer-based learning as any technology-based environment that was used as an instructional tool (e.g., databases, hypermedia, multimedia, and Web-based learning environments) in an educational setting (e.g., classroom) and/or research setting (e.g., laboratory)" (p.579). In Li and Ma (2010), the meta-analysis reviewed the effectiveness of computer technology in K-12 mathematics education. 46 primary studies were included in the analysis from 1990 onward. Overall, computer technology in the mathematics classroom was found to have a small positive effect. There were no significant differences found between different types of technology. Although Schmid et. al. (2014) did find slight differences among different types of educational technology in the postsecondary classroom, they found that overall, all types had a small positive effect. The effects of computer technology on math achievement were most enhanced when used for students with special needs or when used with elementary school students. Studies on the effective use of computer technology for students with special needs found that the technologies used were often multimodal, they were used in small group collaborative activities, and they were used to support modeling of student understanding (Li & Ma, 2010). Even when the technologies studied did not have these attributes, the effects were stronger with special needs students. Finally, Li & Ma's analysis also found that studies published before the turn of the century reported stronger effects of computer technology. This might be due to the novelty effect, to changes in study design and available literature, or it might be due to high expectations of researchers and educators at the time (Li & Ma, 2010). This finding underscores the necessity of continuing and updating the study of effective technology use in mathematics education.

Kupczynski et al. (2011) investigated which factors affect university students' performance in online courses. Specifically, they addressed the relationship between student activity in online courses and grades. The frequency of logins was found to be the most significant variable (among total time and grade level), which accounted for 10.1% of variance in final grades. Dillon-Marable and Valentine (2006) synthesized the literature on effective technology integration in adult basic skills education (ABE), with a focus on literacy skills. Their analysis concluded that a) computer technology should be implemented such that the instructor and students move in a natural way between technology- and non-technology-based portions of lessons; b) the technology should be appropriate for adult learners; c) the technology must be facilitated by instructors; and d) the technology should empower adult learners (Dillon-Marable & Valentine, 2006). This suggests that blended learning may be most appropriate for the ABE classroom. Blended learning incorporates computer-based learning and technology use seamlessly into the classroom. In blended learning, technology is used under the guidance of the instructor, who helps the students build skills. As discussed above, adult learners differ from traditional students in that they are more autonomous individuals, with more specific needs and goals. Thus, it is essential that any technology used serves this central characteristic of adult learners by empowering them.

While there are many barriers to technology access both in and out of the classroom for ABE instructors and learners, calculators are often accessible. One study by Stahl (2011) investigated calculator use by inmates at a correctional facility who were preparing to take the GED. Thirteen students were included in the study, and it was found that the majority of them preferred not to use the calculator to solve problems, and when they did use it, they were much less accurate than when doing mental math. The author concluded that appropriate calculator integration in the GED preparation classes would be necessary in empowering students to use the calculator effectively to solve problems. Instructional support, integration into the curriculum, and appropriate access to technology are critical in the effective application of technology.

Van Laer and Elen (2017) found that the research generally agrees that blended learning environments may offer much-needed flexibility to ABE learners. In their investigation of the relationship between blended learning environments and self-regulatory behaviors in ABE students, they found that cues for self-reflection were most effective in increasing students' self-regulatory behavior, and that these cues were very much lacking from the blended learning environments studied. Self-regulation behavior is related to persistence and motivation and is a hallmark of the adult learner. However, in the case of the ABE learner, these self-regulating skills may be lacking, especially within the context of a blended or online learning environment (Van Laer & Elen, 2017).

2.5 Summary

In summary, the literature indicates that domain-specific self-efficacy can be a useful concept for understanding task-specific performance, especially within academics. Research shows that there is a connection between math self-efficacy and math performance, as well as computer self-efficacy and computer performance. Although literature focusing specifically on the ABE student is not as plentiful, research indicates that computer-based or blended learning may be a valuable tool in adult basic education. ABE students require guidance with becoming skilled at using technology as an aid for academic tasks. However, literature is lacking on the connection specifically between how computer self-efficacy is related to performance on computer-based math tests, particularly within ABE. This study attempts to examine that connection.

CHAPTER 3. METHODOLOGY

3.1 Introduction

This chapter describes the participants, data collection, and design of this study. Ethical considerations and the impact of the Covid-19 pandemic are discussed.

3.2 Participants

The target population of this study was students enrolled in GED classes at an adult education program at a community college in an urban setting in Kentucky. This ABE/ASE program is free and open to any Kentucky resident aged 18 and over who is not enrolled in secondary school. Students enroll in classes in order to earn their GED credential, improve basic skills, or prepare for college. The program serves a high needs population and uses an open-enrollment model, which means that classes run continuously throughout the year without a specific start/end date, and students may join or leave the classes at any time. Participants of the study were enrolled from a subset of the classes available through the program. These were classes taught by the researcher, which cover math-only courses, as well as courses focused on reading/language arts, science, social studies, and math. Classes taught by the researcher were the focus for recruitment because these are the majority of classes at the program that include a math component, and so the participants are a representative sample of the target population. Ethical considerations are addressed below.

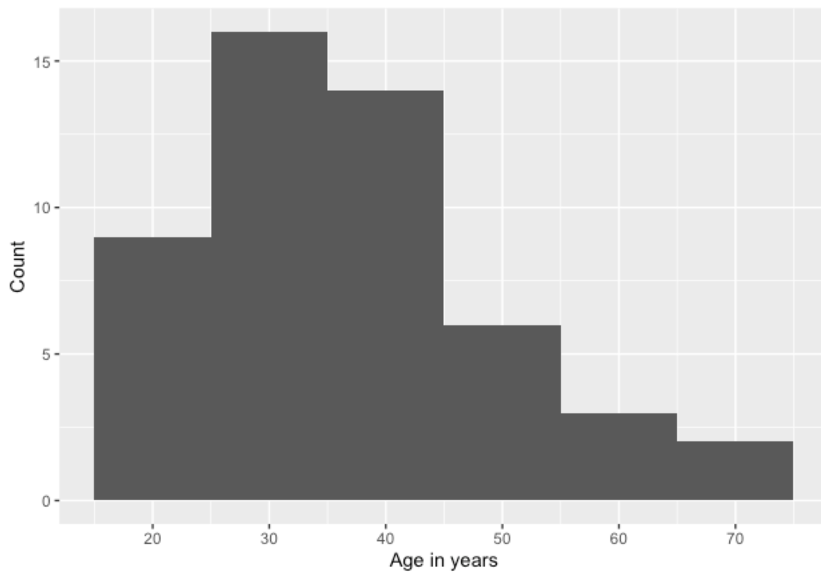
Students enrolling in GED classes take a Test of Adult Basic Education (TABE) during registration in the areas of reading and math, and sometimes language. The TABE 11/12 places students at a National Reporting System (NRS) level ranging from 1 to 6.

NRS levels are used for assessing student progress and in program reporting. NRS levels correspond roughly to grade levels (NRS level 1 corresponds to grade level 0 to 1, NRS level 6 corresponds to grade levels 11 to 12), though grade levels are not commonly used in describing ABE student performance (See Table 3.1). Based on their TABE scores, students may go on to take one or more GED Ready tests (the official GED practice test, which must be passed before taking an actual GED test) before being placed into classes. Once students reach a total of 40 hours of attendance and homework hours, they are eligible to complete the post-test in the TABE subjects with which they enrolled. Students may take GED Ready tests at any time, at the discretion of the student and instructor.

Participants were recruited during their scheduled class times. An experienced ABE instructor at the program described the study, answered questions, and completed the consent process with students. This instructor remained available to participants throughout the study to answer any questions about the study. This instructor maintained secure records of participants and consents throughout the data collection phase of the study, and the researcher did not have access to which individuals were and were not participating in the study. The researcher was not present in the room during recruitment and consent. Students were encouraged to participate in the study by the distribution of $20 Visa gift cards to participants who completed all study requirements. Study requirements aligned with the adult education program requirements.

Most students in this program are working towards earning a GED credential and enter the program at an NRS Level 2 in mathematics (See Figure 4.2). See Table 3.1 for a description of TABE scores and corresponding NRS levels. See Figure 3.1 for the distribution of the ages of study participants. Of the 61 individuals who consented to participate, 59 completed the pre-surveys, 51 completed the pre-surveys and had a valid TABE math pre-test score from the year of the study. Of those, 48 completed at least one EdReady (see section 3.4) class, and 21 completed at least one post-survey.

Figure 3.1 Age distribution of study participants



3.3 Data Collection and the Covid-19 Pandemic

The data used in this study was obtained from several sources. Pre-surveys and post-surveys were collected from participants regarding computer and mathematics self-efficacy. TABE, GED Ready, and GED test scores were collected using the KAERS database. Test scores were considered valid pre-test scores if the test date was between the start of the program year (July 2019) and the date of the participant's pre-survey. Test scores were considered valid post-test scores if the test date was after the date of the participant's pre-survey and beginning use of the EdReady program (see section 3.4) and before the end of the program year (June 2020). Reports of participant use of the

EdReady online learning program, including learning progress, dates, and duration of use, were recorded. Number of EdReady class sessions attended were recorded for each participant. Students began using the EdReady program during each class meeting after they had completed the pre-surveys. Both math and computer self-efficacy pre-surveys and post-surveys were collected. Due to the open-enrollment nature of the program and the characteristics of the target population, not all data were collected from all participants. Further, administration of pre-surveys and use of the EdReady program began shortly before all learning went fully remote due to the Covid-19 pandemic. The original data collection timeline planned for participants to be continuously enrolled starting January through the end of February, with participants completing pre-surveys and beginning in-class use of the EdReady online learning program. In-class use of EdReady was planned to continue through the end of May 2020, and post-surveys were going to be administered either after 15 in-class EdReady sessions or at the end of May and beginning of June, whichever came first. However, the closure in early March 2020 ended all in-person classes, and all TABE and GED testing was suspended. Remote GED Ready testing continued but required use of a personal computer and internet. 23 participants logged in to EdReady after the closure began. Three participants took a TABE post-test before testing stopped. Self-efficacy post-surveys were administered online beginning June. Because of the difficulty of technology access and drop in program participation, there was a corresponding drop in the number of post-surveys successfully completed by participants (21 participants had at one or both post-surveys). Of the 23 students who logged in to EdReady after the closure began, 13 of them were included in those who completed post-surveys. Lack of post-test and post-survey data affected the analysis and results of this study.

3.4 Measurement

Test score information was gathered using the KAERS database, maintained by Kentucky Skills U. The Test of Adult Basic Education (TABE) version 11/12 is comprised of three subjects: mathematics, reading, and language. The TABE is available in levels L, E, M, D, and A, and the appropriate level is determined by an initial locator test in each subject. The TABE score report includes a scale score (300 – 800) and corresponding National Reporting System (NRS) level (1-6). See Table 3.1. NRS levels are developed and used by the National Reporting System for Adult Education, an accountability system for adult education programs funded federally through the Workforce Innovation and Opportunity Act (WIOA) (National Reporting System, 2019). Each NRS level corresponds approximately to a range of two grade levels. NRS level 1 corresponds to a grade level of kindergarten/1st grade. NRS level 6 corresponds to a grade level of 11/12 (National Reporting System, 2019). A mathematics and reading score are required for registration in the program. A student may register with only one of these subjects if they have already passed GED subjects in other areas and/or only intend to study in one subject area. The TABE is administered as a computer-based test for the majority of test-takers in this program and was administered as a computer-based test for all study participants.

Table 3.1 TABE levels, scale scores, and NRS levels for Math and Reading

Mathematics						
	NRS Level 1	NRS Level 2	NRS Level 3	NRS Level 4	NRS Level 5	NRS Level 6
TABE L	300 - 448	449 - 495				
TABE E	310 - 448	449 - 495	496 - 536			
TABE M		449 - 495	496 - 536	537 - 595		
TABE D			496 - 536	537 - 595	596 - 656	
TABE A				537 - 595	596 - 656	657 - 800
Reading						
	NRS Level 1	NRS Level 2	NRS Level 3	NRS Level 4	NRS Level 5	NRS Level 6
TABE L	300 - 441	442 - 500				
TABE E	300 - 441	442 - 500	501 - 535			
TABE M		442 - 500	501 - 535	536 - 575		
TABE D			501 - 535	536 - 575	576 - 616	
TABE A				536 - 575	576 - 616	617 - 800
Adapted from Data Recognition Corporation (2019)						

The 2014 version of the GED Exam was developed by Pearson Vue and the GED Testing Service. The GED Ready is the official practice test of the GED. In Kentucky, an individual must pass the GED Ready in a given subject before attempting the GED in that subject. The GED is comprised of four timed subjects: Reasoning Through Language Arts, Mathematical Reasoning, Social Studies, and Science. The GED and GED Ready are administered as computer-based tests through a test-taker's online GED account. Scores range from 100-200, and 145 is the passing score. A 145 must be achieved in each subject. The subjects may be taken individually. An individual may take the GED Ready test at any time, though students enrolled in this program site are encouraged to take GED Ready tests based on their TABE scores and classwork performance. Of the test scores collected, TABE math scores were the primary focus, as 51 of 61 participants had valid pre-test TABE math scores. Additionally, the purpose of the TABE is to gauge the basic math skill level of adult students, which is more closely related to overall math performance than the GED test, which is more narrowly focused on high school equivalency.

EdReady is an online learning platform developed and maintained by the NROC project. Kentucky Skills U has contracted with NROC to provide EdReady to its students at no cost. EdReady for ABE students provides personalized GED and college math and English readiness platform designed to help learners test their GED and college readiness and work on a personalized learning path to fill in knowledge gaps. Kentucky Skills U provides multiple curriculum products as options to programs, but EdReady was chosen by the researcher for three reasons. First, it has unlimited 'seats', and so it could accommodate registration of all students in the researcher's classes. Second, it provides relevant learning pathways for the researcher's students' goals. Most students worked on the 'GED Math High Impact Indicators' pathway, which focuses on improving math skills deemed most applicable ('high impact') by the GED Testing Service. Other pathways are available, including ones for college math readiness and pathways focused on specific TABE Math levels. Third, EdReady includes accessibility features such as screen reader support, ability to adjust display color, size, and contrast, as well as multimodal presentation of learning material (video with captions, text). After completing self-efficacy pre-surveys, students began using the EdReady platform during classes. The researcher was present during classes to assist students with the necessary computer skills and math learning. Students used laptop computers and headphones for learning with the EdReady program during class. Computer mice were available for students who preferred it over the laptop touchpad. Students used the EdReady program during each class meeting of the data collection period. Students were also able to use EdReady for study at home, if they had access with computer and internet. Students without this home access were provided with paper homework related to their current EdReady progress and test preparation.

Surveys were administered at the beginning of the data collection period, as well as after students had begun using the EdReady program during classes. The pre- and post-surveys were used to measure students' computer and math self-efficacy. The computer self-efficacy survey is an adapted form of the Computer User Self-Efficacy (CUSE) Scale (Cassidy & Eachus, 2002). This survey was originally developed and validated using a population of undergraduate, graduate, and professional adults. The survey includes two parts. The first part assesses the individual's computer experience. Of the five items, item two asks the respondent to rate their experience with computers on a scale from 1 to 5, where 1 = None, 2 = Very limited, 3 = Some experience, 4 = Quite a lot, 5 = Extensive. Part two (30 items) assesses computer self-efficacy using a Likert-type scale ranging from 1 (Strongly Disagree) to 6 (Strongly Agree) (See Appendix 1). The math self-efficacy survey is an adapted form of the Sources of Middle School Mathematics Self-Efficacy (SMSMSE) Scale (24 items) (Usher & Pajares, 2009). The survey uses a Likert-type scale ranging from 1 (Definitely False) to 6 (Definitely True). It includes four subscales representing four sources of self-efficacy: mastery experience, vicarious experience, social persuasions, and physiological state (See Appendix 2). Both surveys are modified slightly to be appropriate for the study's target population of current ABE learners. Pre-surveys were administered on paper. Post-surveys were administered online due to the Covid-19 closure using the Qualtrics platform, and were accessible via smartphone, tablet, and computer.

3.5 The Study Design

Of those who consented to participate in the study, 59 completed self-efficacy pre-surveys. Of those who had complete pre-surveys, 51 had a valid pre-test TABE math score, and of those, 48 used the EdReady program at least once during the data collection period. Of those with pre-surveys, valid pre-test TABE math scores, and EdReady use, 16 completed self-efficacy post-surveys. Three total participants had valid post-test TABE math scores.

The variables used in analysis were plotted and described. This study used simple linear regression and multiple linear regression to investigate the following relationships:

Age and performance
Self-efficacy and performance
EdReady use and change in self-efficacy
Initial self-efficacy and change in self-efficacy

Simple linear regression was also used to verify the relationship between computer self-efficacy and math self-efficacy, and well as the relationship between computer experience and computer self-efficacy. The data on number of EdReady sessions and change in math performance was plotted and described, due to small sample size (n=3).

3.6 Ethical Considerations

The target population of this study includes adult students working to develop basic reading and mathematics skills. Some study participants may therefore be considered economically or educationally disadvantaged persons. Safeguards were included in this study to protect the rights and welfare of study participants. First, it is important that the consent process be accessible and understandable for all potential participants. In developing the consent form, the study team balanced clear, simple language while including all necessary information. The consenting process was conducted by an experienced ABE instructor, who is familiar with the program and the students. This instructor was available to answer all questions during the consent process, as well as throughout the study. Second, it is important that the study is not exploitative. Study participants had the same class experience as all other students. Participants completed class activities, homework, and testing as directed by their instructor and the program guidelines. Participation in the study involved minimal risk (student data was collected and stored) and reward (participants completing all requirements were eligible to receive a $20 gift card). The reward encouraged participants to do things that they would already be expected to do as students in the program (attend classes, complete coursework, complete testing). Third, care was taken to avoid coercion. The researcher, who is also the students' instructor, did not have knowledge of who chose to participate in the study throughout the data collection period. This anonymity was made clear to students during the consent process. This measure was intended to avoid the possibility that students feel pressured into participating due to their relationship with their instructor (the researcher is their instructor).

The researcher was given access to participant data only after all survey, homework and classroom participation, and testing was complete. As these classes are not graded and there is no start and end date, it was not possible to wait until the end of the class for the researcher to receive participant data.

CHAPTER 4. RESULTS

4.1 Introduction

This chapter describes the variables used in analysis. The regression analysis is described, and results are discussed. Analysis was performed using RStudio version 1.4.1106.

4.2 The Variables

Table 4.1 gives a list of the variables used in analysis along with a description of each.

Table 4.1 Description of variables

Variable name	***Description***
age	Age in years
pre_math_score	TABE Math pre-test scale score (300 – 800 points)
pre_read_score	TABE Reading pre-test scale score (300 – 800 points)
pre_comp_se	Pre-survey computer self-efficacy score (total score based on 30 Likert-type items) (30 – 180 points)
pre_math_se	Pre-survey math self-efficacy score (total score based on 24 Likert-type items)(24 – 144 points)
pre_me	Pre-survey math mastery experience subscale score (total based on 6 Likert-type items)(6 – 36 points)
pre_ve	Pre-survey math vicarious experience subscale score (total based on 6 Likert-type items) (6 – 36 points)
pre_p	Pre-survey math social persuasions subscale score (total based on 6 Likert-type items) (6 – 36 points)
pre_ph	Pre-survey math physiological state subscale score (total based on 6 Likert-type items) (6 – 36 points)
change_comp_se	Change in computer self-efficacy scores from pre- to post-survey
change_math_se	Change in math self-efficacy scores from pre- to post-survey

change_me	Change in math mastery experience subscale scores from pre- to post-survey
change_ve	Change in math vicarious experience subscale scores from pre- to post-survey
change_p	Change in math social persuasions subscale scores from pre- to post-survey
change_ph	Change in math physiological state subscale scores from pre- to post-survey
er_classes	Number of EdReady class sessions attended
er_logins	Number of EdReady log-ins
er_hours	Number of hours spent logged in to EdReady
post_math_score	TABE Math post-test scale score (300 – 800 points)

4.3 Descriptive Analysis

Histograms and scatterplots were used for initial inspection of the data. The mean age of the 59 participants who completed pre-surveys was 37 years. The minimum age was 18 and the maximum age was 71. Further summary data of variables is shown in Table 4.2. A heatmap of Pearson correlation coefficients is shown in Figure 4.1.

Table 4.2 Summary data of variables

	Min.	*Median*	*Mean*	*Max.*	*Std. dev.*
age	18	36	37	71	12.64
pre_math_score	419	485	490	548	27.43
pre_read_score	413	494	498	597	37.93
pre_comp_se	35	123	123	180	32.64
pre_math_se	35	86	85	139	22.72
pre_me	6	18	19	35	7.49
pre_ve	6	26	26	36	7.27
pre_p	6	14	16	36	8.14

pre_ph	6	24	24	36	8.38
change_comp_se	-49	2	8.8	105	39.41
change_math_se	-33	4	6.7	47	19.14
change_me	-17	2	1.2	13	6.98
change_ve	-9	1	3	18	6.67
change_p	-11	1	1.8	15	6.78
change_ph	-19	-1	0.8	20	9.01
er_classes	0	4	5	15	3.87
er_logins	0	10	17	125	19.92
er_hours	1	9	14	70	15.99

Figure 4.1 Heatmap of Pearson correlation coefficients, ‘x’ indicates insignificant at the .05 level

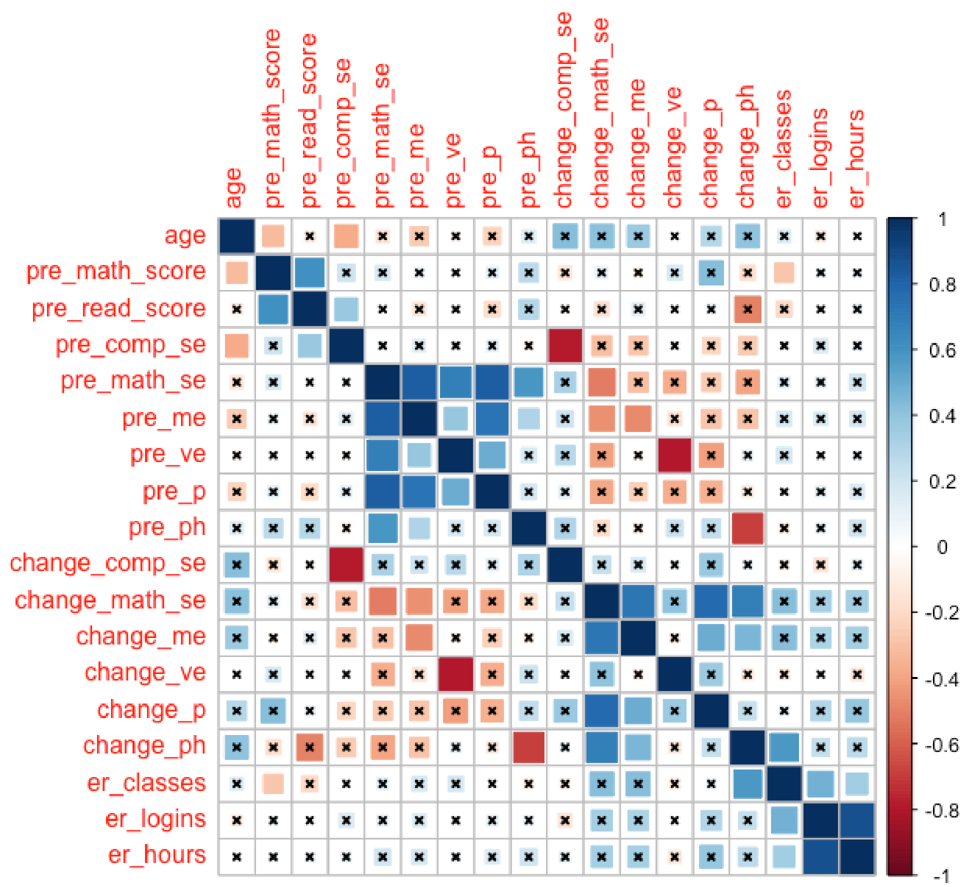


Figure 4.2 Histogram of TABE Math pre-test scale scores with NRS levels

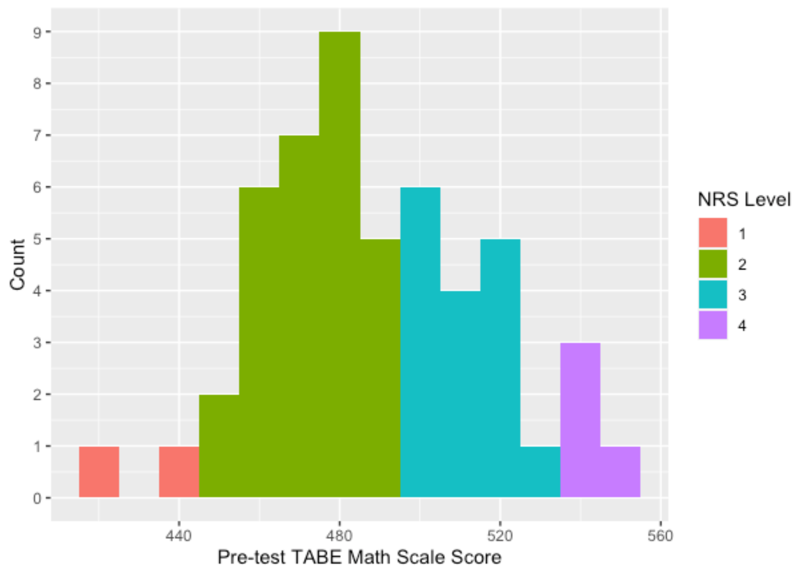
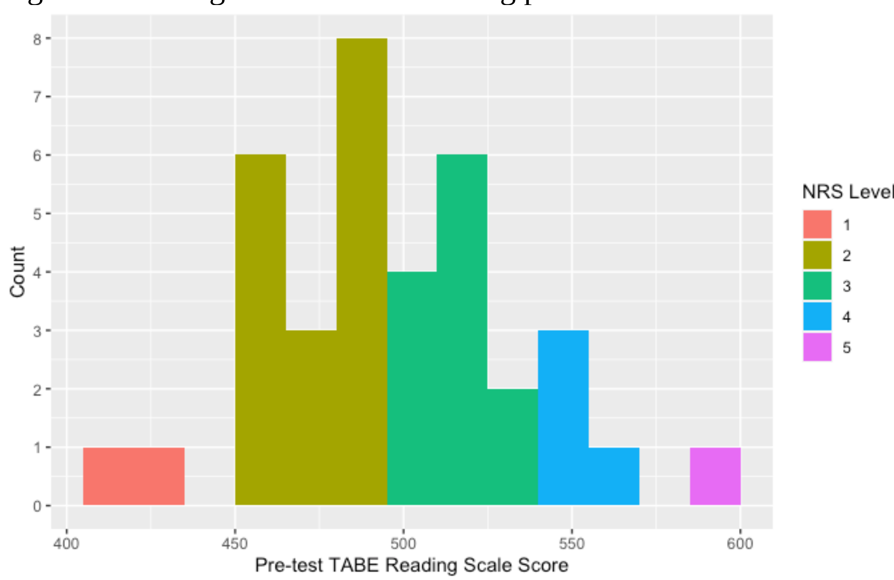


Figure 4.3 Histogram of TABE Reading pre-test scale scores with NRS levels

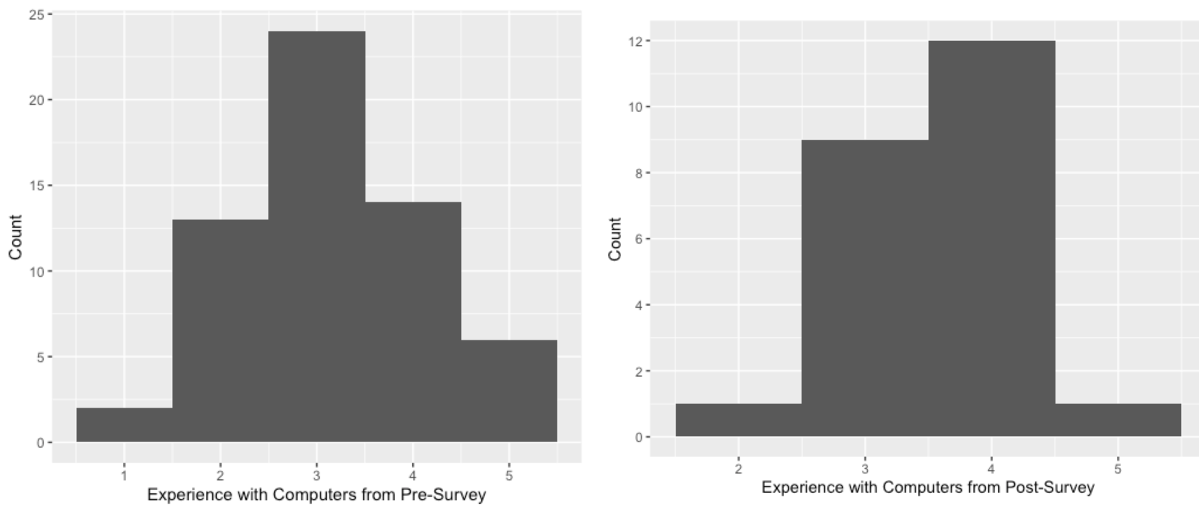


For both reading and math pre-test scores, most participants fell within NRS level 2, or approximately a grade level 2 or 3. Most participants were between 25 and 45 years of age.

On the pre-survey, 41% of respondents reported having 'Some Experience' with computers, and 24% reported 'Quite a lot' of experience. On the post-survey, 39%

reported ‘Some Experience’ and 52% reported ‘Quite a lot’ of experience. These shifts in proportion are reflected in the histograms shown in Figure 4.4. Mitigating factors in the post-survey results are discussed in Chapter 5.

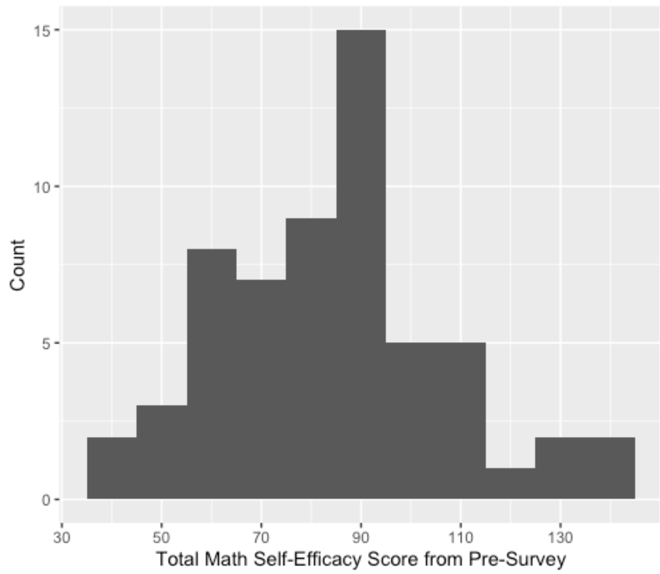
Figure 4.4 Histograms of Computer Experience



Pre_math_score has a mean of 490, a standard deviation of 27.43, and a minimum and maximum value of 419 and 548, respectively. Examining the histogram in Figure 4.2, we see that the scores for *pre_math_score* are approximately normal. *Pre_read_score* has a mean of 498, a standard deviation of 37.93, and a minimum and maximum value of 413 and 597, respectively. Examining the histogram in Figure 4.3, we see that the scores for *pre_read_score* are approximately normal. *Pre_read_score* was used for comparison purposes with *pre_math_score* in the regression models.

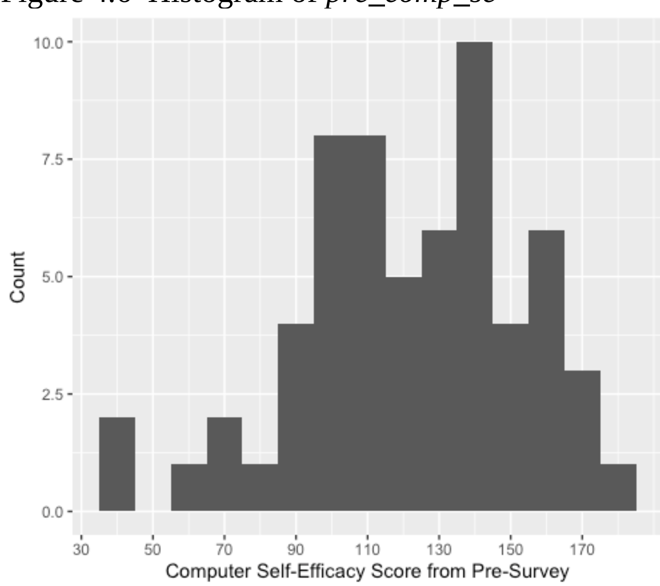
Pre_math_se has a mean of 85, a standard deviation of 22.72, and a minimum and maximum value of 35 and 139, respectively. Examining the histogram in Figure 4.5, we see that the scores for *pre_math_se* are slightly skewed to the lower end of the scale. See Table 4.2 for summary statistics of *pre_me_se*, *pre_ve_se*, *pre_p_se*, and *pre_ph_se*.

Figure 4.5 Histogram of *pre_math_se*



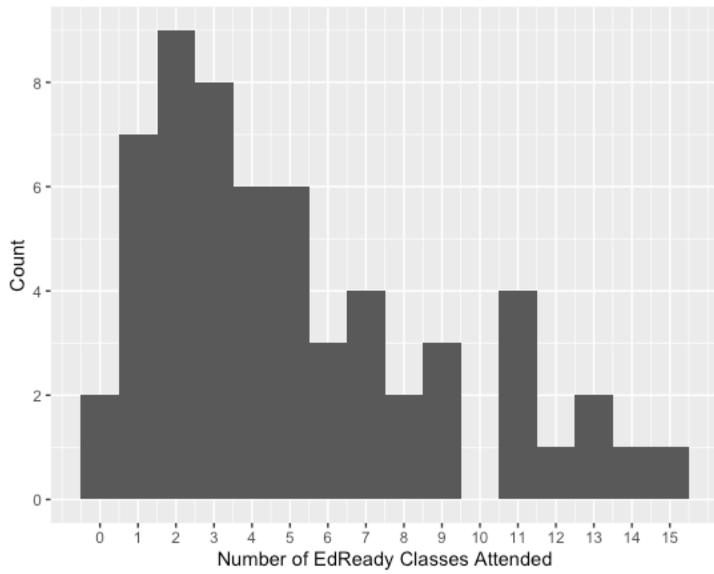
Pre_comp_se has a mean of 123, a standard deviation of 32.64, and a minimum and maximum value of 35 and 180, respectively. Examining the histogram in Figure 4.6, we see that the scores for *pre_comp_se* are slightly skewed to the higher end of the scale.

Figure 4.6 Histogram of *pre_comp_se*



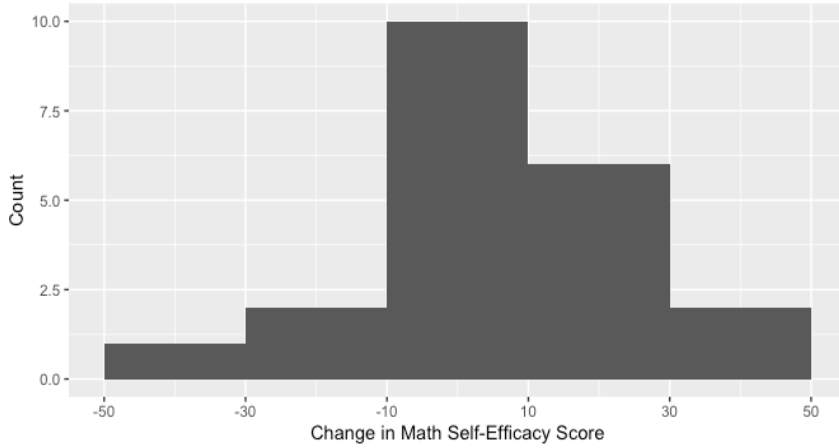
Er_classes has a mean of 5, a standard deviation of 3.87, and a minimum and maximum value of 0 and 15, respectively. Examining the histogram in Figure 4.7, we see that the numbers for *er_classes* are skewed to the lower end of the scale. See Table 4.2 for summary statistics of *er_logins*, and *er_hours*. These variables were used for comparison purposes with *er_classes*.

Figure 4.7 Histogram of *er_classes*



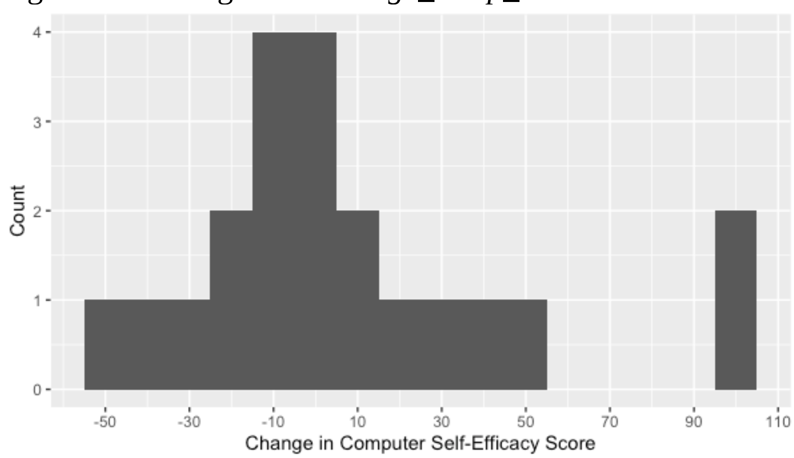
Change_math_se has a mean of 6.7, a standard deviation of 19.14, and a minimum and maximum value of -33 and 47, respectively. Examining the histogram in Figure 4.8, we see that the scores for *change_math_se* are slightly skewed to the positive end of the scale.

Figure 4.8 Histogram of *change_math_se*



Change_comp_se has a mean of 8.8, a standard deviation of 39.41, and a minimum and maximum value of -49 and 105, respectively. Examining the histogram in Figure 4.9, we see that the scores for *change_comp_se* are skewed to the positive end of the scale due to two unusually high changes.

Figure 4.9 Histogram of *change_comp_se*



4.3.1 Age, Performance, and Self-Efficacy

Plots indicated a weak positive correlation between pre-survey computer self-efficacy and math pre-test scores, along with pre-survey computer self-efficacy and reading pre-test scores. The plots indicated weak positive correlations between pre-survey math self-efficacy and math pre-test scores, along with pre-survey math self-efficacy and reading pre-test scores. See Figure 4.10 below for scatterplots. The Pearson correlation coefficients indicated a weak positive but insignificant (at the .05 level) correlation between math performance and computer self-efficacy ($r = .21$, $p = .140$). The Pearson correlation coefficients indicated a weak positive and significant relationship between reading performance and computer self-efficacy ($r = .375$, $p = .024$). The Pearson correlation values indicated negative and significant relationships between math performance and age ($r = -0.32$, $p = 0.02$), as well as computer self-efficacy and age ($r = -0.34$, $p = 0.003$). The Pearson correlation values indicated a negative, weak, and insignificant correlation between reading performance and age ($r = -0.09$, $p = 0.60$), as well as between math self-efficacy and age ($r = -0.13$, $p = 0.32$). See Figure 4.11. See Figure 4.1 for heatmap of Pearson correlation coefficients with significance indicators.

Figure 4.10 Scatterplots of performance vs. computer and math self-efficacy

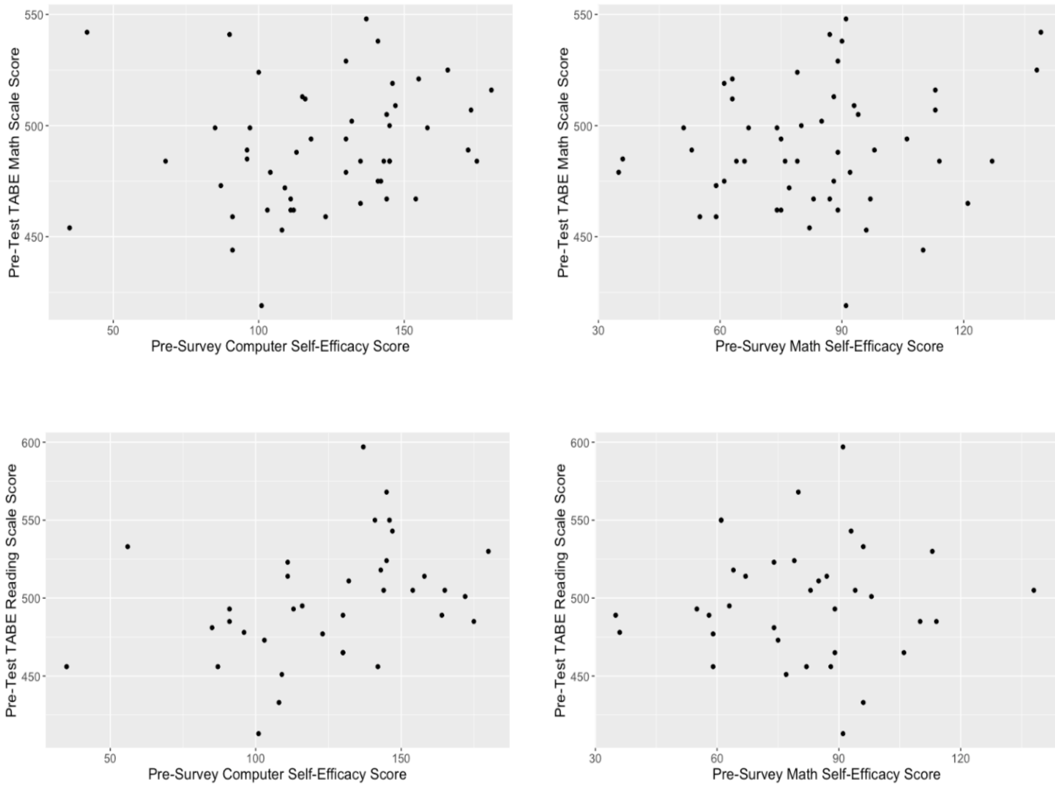
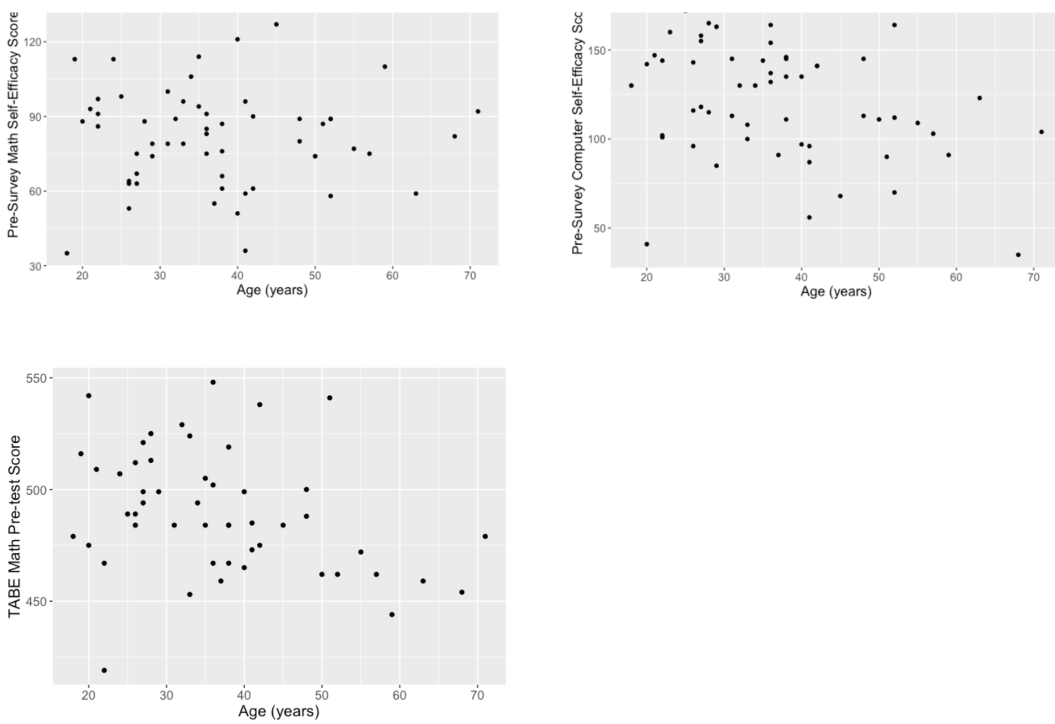


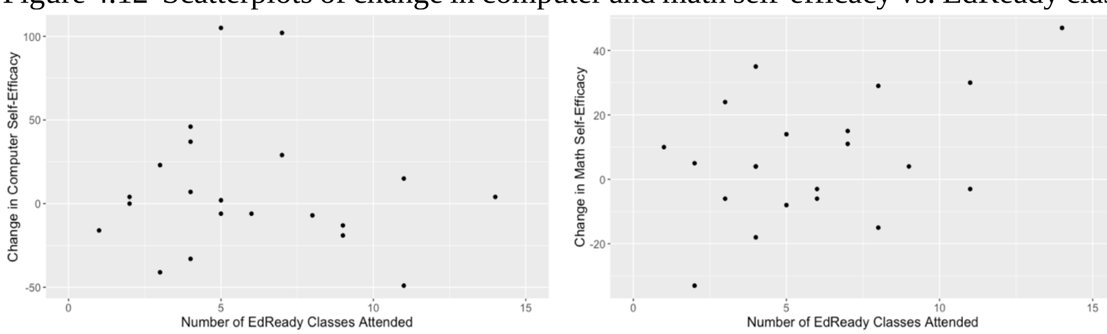
Figure 4.11 Scatterplots of computer and math self-efficacy and performance vs. age



4.3.2 Self-Efficacy and EdReady Use

Use of the EdReady program was recorded in three ways – numbers of classes attended where the student logged in to the EdReady program, total number of log-ins during the data collection period, and total hours logged during the data collection period. Number of EdReady classes attended ranged from 0 to 15. The correlation between change in computer self-efficacy and number of EdReady classes was weak, negative, and insignificant ($r = -0.07$, $p = 0.75$). The correlation between change in math self-efficacy and number of EdReady classes was moderate and positive, but insignificant at the .05 level ($r = 0.42$, $p = 0.06$). See scatterplots in Figure 4.12. The relationships between computer and math self-efficacy and both EdReady log-ins and total hours were not appreciably different from the relationships with number of EdReady classes.

Figure 4.12 Scatterplots of change in computer and math self-efficacy vs. EdReady classes



Inspection of vertical line plots comparing pre- and post-survey computer and math self-efficacy scores with EdReady use indicated a possible relationship between pre-survey scores and change in scores. See Figures 4.13 and 4.14. It appeared that participants with low computer self-efficacy possibly tended to experience more positive change in computer self-efficacy compared to participants with higher starting computer self-efficacy. A similar relationship appeared possible in the math self-efficacy vertical line plot.

Figure 4.13 Change in computer self-efficacy vs. EdReady classes

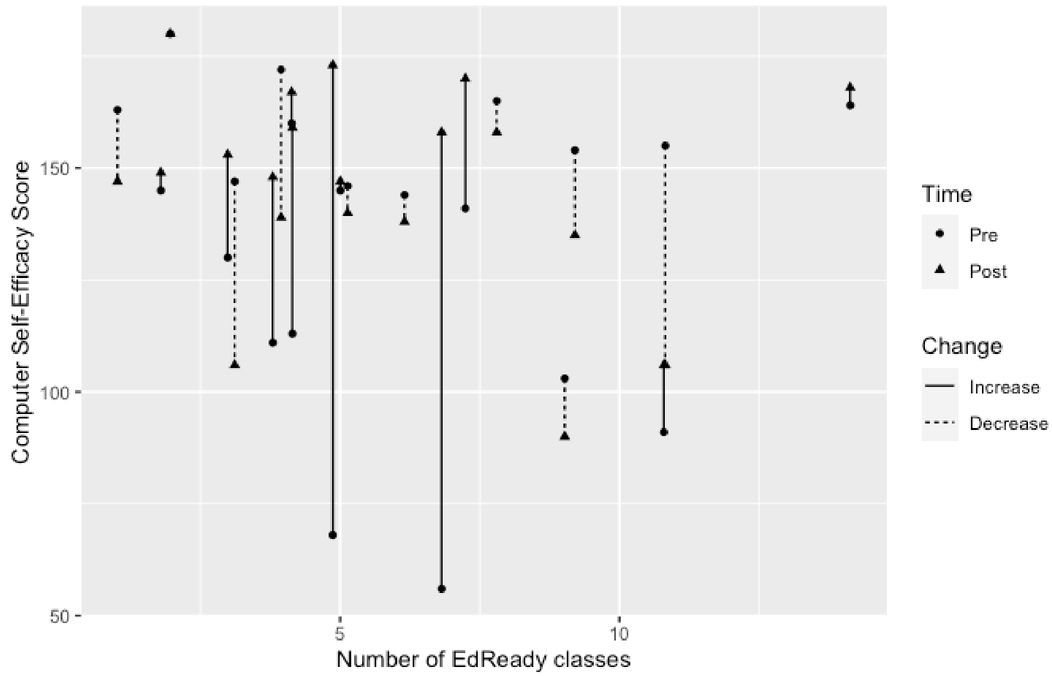
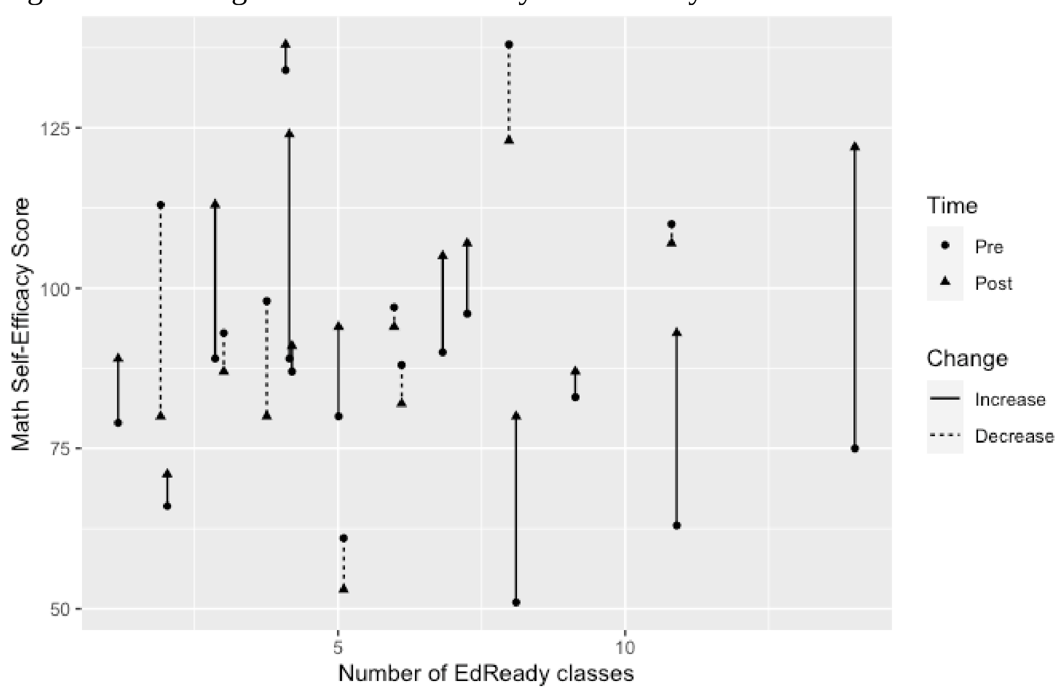


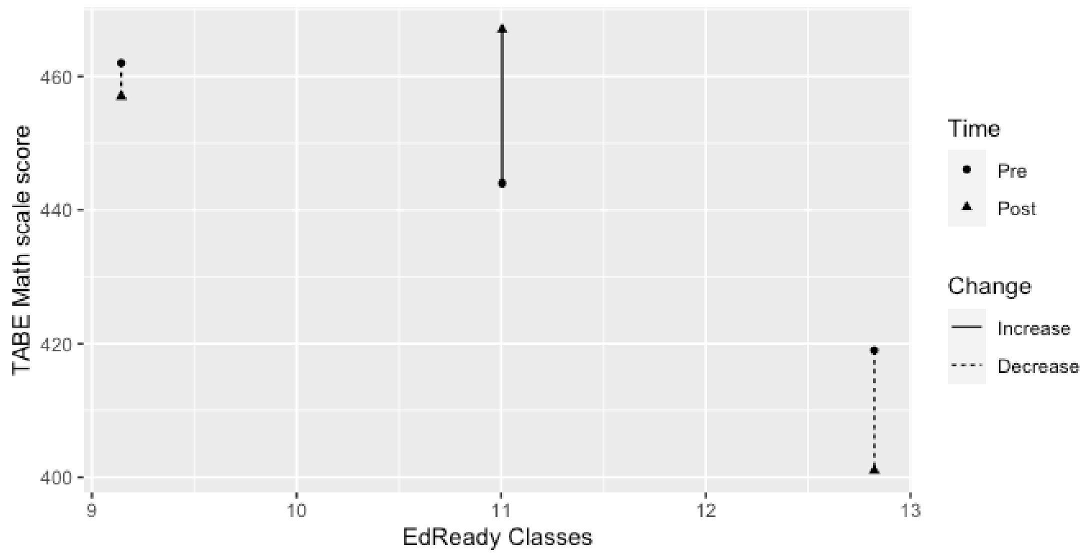
Figure 4.14 Change in math self-efficacy vs. EdReady classes



4.3.3 Math Performance and EdReady Use

Three math post-tests were collected, and the vertical line plot showing pre- and post-test math scores versus EdReady classes is shown in Figure 4.15.

Figure 4.15 Change in math performance vs. EdReady classes



4.4 Regression Analysis

Linear regression was used to investigate research questions one and two. Significance was evaluated at the .05 alpha level. In the tables shown, standard errors and p-values are included in parentheses (standard error, p-value). Intercepts are not described, as they are not meaningful for this study.

4.4.1 Performance, Age, and Self-Efficacy

First, the relationship between math performance, age, and computer and math self-efficacy was investigated. The models using *pre_math_score* as a response variable are shown in Table 4.3. The results of the linear regression for Model 1 show that on average, a one-point increase in math self-efficacy score results in a predicted increase of .19 TABE math scale score points. However, the slope coefficient of *pre_math_se* is not statistically significant at the .05 level (p = .25).

Table 4.3 Linear models with *pre_math_score* as response

	Model 1	Model 2	Model 3	Model 4	Model 5
Pre_math_se	0.19 (0.17, 0.25)				0.15 (0.16, 0.33)
Pre_comp_se		0.18 (0.12, 0.14)			0.08 (0.13, 0.57)
Age			-0.68* (0.29,0.02)		-0.58 (0.32, 0.08)
Pre_comp_exp				0.59 (3.85, 0.88)	

*p < .05; **p < .01

In Model 2, the results of the linear regression show that on average, a one-point increase in computer self-efficacy score results in a predicted increase of .18 TABE math scale score points. The slope coefficient of *pre_comp_se* is not statistically significant at the .05 level (p = .14).

In Model 3, the results of the linear regression show that on average, a one-year increase in age results in a predicted decrease of .68 TABE math scale score points. The slope coefficient of age is statistically significant at the .05 level (p = .02).

In Model 4, the results of the linear regression show that on average, a one-point increase in computer experience score results in a predicted increase of 0.59 TABE math scale score points. The slope coefficient of *pre_comp_exp* is not statistically significant at the .05 level (p = .88).

In Model 5, the multiple linear regression results did not differ appreciably from the simple linear regression models (See Table 4.3).

Table 4.4 Linear models with *pre_read_score* as response

	Model 6	Model 7	Model 8	Model 9
Pre_math_se	0.018 (0.30, 0.95)			-0.14 (0.29, 0.64)
Pre_comp_se		0.44* (0.18, 0.02)		0.52* (0.22, 0.02)
Age			-0.27 (0.51, 0.60)	0.33 (0.55, 0.55)

*p < .05; **p < .01

In Model 7, the results of the linear regression show that on average, a one-point increase in computer self-efficacy results in a predicted increase of 0.59 TABE reading scale score points. The slope coefficient of *pre_comp_se* is statistically significant at the .05 level (p = .02). Models 6, 8, and 9 did not reveal any further significant relationships involving reading scores.

4.4.2 Self-Efficacy and EdReady Use

Next, the relationship between computer and math self-efficacy and EdReady use was investigated using simple linear regression. In Model 10, the results of the linear regression show that on average, attending one additional EdReady class results in a predicted change in math self-efficacy score of 2.40 points. See Table 4.5.

Table 4.5 Linear models with *change_math_se* as response

	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Er_classes	2.40 (1.19,0.06)					1.96 (1.06,0.08)
Er_logins		0.23 (0.15,0.14)				
Er_hours			0.31 (0.19,0.13)			
Pre_math_se				-0.45* (0.17,0.02)		-0.39* (0.16,0.03)
Pre_comp_se					-0.19 (0.14,0.18)	-0.11 (0.12,0.08)

*p < .05; **p < .01

Table 4.6 Linear models with *change_comp_se* as response

	Model 16	Model 17	Model 18	Model 19	Model 20
Er_classes	-0.84 (2.64,0.75)				-2.10 (1.63,0.22)
Er_logins		-0.20 (0.33,0.54)			
Er_hours			0.17 (0.41,0.68)		
Pre_comp_se				-0.92** (0.17,2.5e-5)	-0.95** (0.17,1.9e-5)

*p < .05; **p < .01

Table 4.7 Linear model with *pre_comp_se* as response

	Model 21
Pre_comp_exp	16.28** (3.85,8.6e-5)

*p < .05; **p < .01

In Model 16, the results of the linear regression show that on average, attending one additional EdReady class results in a predicted change in computer self-efficacy score of -.85 points. The slope coefficient of *er_classes* is not statistically significant at the .05 level (p = .75). See Table 4.6.

Changes in computer and math self-efficacy were also modeled using number of EdReady log-ins and number of EdReady hours as predictors. However, the models were not found to be different in any significant ways from using EdReady classes. See Tables 4.5 and 4.6.

4.4.3 Self-Efficacy Scores and Change in Self-Efficacy

Because initial inspection of the vertical line plots (Figures 4.13 and 4.14) indicated a possible negative relationship between change in computer and math self-efficacy and pre-survey self-efficacy score, this relationship was further investigated using linear regression. In Model 19, the results of the linear regression show that on average, one additional point in the pre-survey computer self-efficacy score results in a predicted change in computer self-efficacy score of -.91 points. The slope coefficient of *pre_comp_se* is statistically significant at the .05 level ($p = 2.5 \times 10^{-5}$). The results of the multiple linear regression in Model 20 were not meaningfully different from the simple linear regression in Models 16 and 19. See Table 4.6.

In Model 13, the results of the linear regression show that on average, one additional point in the pre-survey math self-efficacy score results in a predicted change in math self-efficacy score of -.45 points. The slope coefficient of *pre_math_se* is statistically significant at the .05 level ($p = .02$). See Table 4.5.

In Model 14, the results of the linear regression show that on average, one-point additional point in the pre-survey computer self-efficacy score results in a predicted change in math self-efficacy score of -.19 points. The slope coefficient of *pre_comp_se* is not statistically significant at the .05 level ($p = .18$).

The multiple linear regression in Model 15 was not meaningfully different from the simple linear regressions in Models 10, 13, and 14.

CHAPTER 5. DISCUSSION AND CONCLUSION

5.1 Introduction

This study aimed to understand the relationships between computer and math self-efficacy, math performance, and guided in-class use of an online educational program (EdReady). Of particular interest was the relationship between math performance on computer-based tests and computer self-efficacy, as ABE students are increasingly required to take tests such as the TABE and GED on computers. Here the research questions are reiterated:

1. How do computer and math self-efficacy impact ABE student math performance on computer-based tests?
2. How does weekly, guided, in-class use of an online educational program affect ABE student computer and math self-efficacy?
3. How does weekly, guided, in-class use of an online educational program affect ABE student math performance?

5.2 Discussion

5.2.1 Age, Self-Efficacy, and Performance

First and unsurprisingly, age had a negative and significant relationship to math performance and computer self-efficacy. Possibly an older student may be more likely to feel uncertain about their ability to perform tasks with computers. It also possibly indicates that though older students may have been using numeracy skills throughout their life, they may remember less or feel less confident about their skills with formal mathematics. The current TABE test is closely aligned with current national mathematics standards and practices (College and Career Readiness, 2019; Pimentel, 2013), which looks different from what older students learned when they were originally in school (Porter et al., 2011; Schmidt & Houang, 2012). The relationship between age and math self-efficacy was also negative, but not statistically significant. This may indicate that more data is needed, or it may be the case that there is less of a difference in students' math self-efficacy with respect to age. Perhaps a relatively strong sense of self-efficacy is required to cause a student to return to school and take a math test when they have been out of school and not studying formal mathematics for many years. Maybe an older student does not feel as confident about their skills respective to formal or more advanced math, but maybe their math self-efficacy has at the same time been bolstered by more years of applying numeracy skills in their daily life.

Both math and computer self-efficacy were found to have a statistically insignificant impact on math performance. Although the regression model was insignificant, the relationships between math performance and self-efficacy were slightly positive, which aligns with expectations that domain-specific self-efficacy is a meaningful predictor of academic performance (Pajares, 1996; Bandura & Locke, 2003; Bandura, 1997). Of particular interest is the relationship between math performance and computer self-efficacy, since students are taking math tests on computers. Although domain-specific self-efficacy is established in the literature as a strong predictor of academic performance, maybe the specific characteristics of the ABE population warrants inclusion of other constructs in analysis, such as math anxiety and self-concept. One reason this studied focused solely on self-efficacy was to ensure that surveys were not overly long and taxing for participants. A future study could exclude math self-efficacy but include survey items related to other constructs besides computer self-efficacy.

Relatedly, perhaps the relationship between math performance on computer-based tests and computer self-efficacy may be more evident if a broader sample of adults without a high school credential were given TABE tests and surveys. This could include adults not currently interested in seeking a GED and/or attending classes, and adults who begin the GED-seeking process by taking the TABE test but do not persist.

Computer experience was found to have a statistically insignificant impact on math performance, but it was very significantly related to computer self-efficacy. This reflects the insignificant relationship between computer self-efficacy and math performance.

This complex relationship between computer self-efficacy and math performance is reflected elsewhere in the literature on ABE students. Southerlin (2016) found in interviews with first-time GED test-takers that overall the individuals felt confident about their computer skills and that they did not feel they needed to practice with the computer before taking the computer-based GED tests for the first time. The individuals in Southerlin's study expressed that they felt they had high computer self-efficacy, and also that any lack of experience they had would not be very relevant to their performance on the computer-based GED test. Southerlin also found the relationship between computer self-efficacy and math performance to be insignificant (though it was significant for performance on the Reasoning through Language Arts and Science sections of the GED test) (Southerlin, 2016). It seems unlikely that language arts and science would have a significant relationship to computer self-efficacy where math and social studies do not. Southerlin's findings again show that the complexity of how computer self-efficacy interacts with subject matter performance on computer-based tests, especially within the under-studied ABE population will require more time and data collection. The results parallel the results in this study in that computer self-efficacy was not found to be a significant predictor of math performance and presents some perhaps surprising characteristics of the study population. Perhaps some other demographic and/or psycho-social factors are relevant but were not included in the current study.

A possible explanation for the insignificant findings in this study with respect to research question one is the wide range of dates over which pre-test scores were collected (eight months), and thus the great variation between when the test was taken and when the self-efficacy surveys were taken. Another possible factor is whether or not the participant had taken the TABE test before and how many times. Some students have been in the program off and on for many years. Additionally, variation in when students began attending classes and whether or not they had used computers in class prior to the beginning of the study may have influenced the relationship between self-efficacy and performance. Some participants gained experience with computers and spent time studying math between their pre-test and pre-survey, while others did not. Further, the data did not include individuals who took initial TABE tests but did not enroll in classes (either because they proceeded straight to GED testing and passed, or because they stopped participating). A future study should administer computer and math self-efficacy surveys to first-time TABE test-takers at the time of their first test to collect data on a broader sample of individuals at the ABE level and to more accurately reflect the connection between computer self-efficacy and math performance at the time of the math test.

5.2.2 Self-Efficacy and EdReady Use

Participation in guided in-class use of an online educational program was found to have a statistically insignificant effect on computer self-efficacy and math self-efficacy. However, the relationship between number of EdReady classes and change in math self-efficacy was positive and had a p-value of 0.06. This may indicate that in general, attending classes had a positive impact on math self-efficacy, or it may have been specifically related to use of the EdReady program in class. A future study would include data from participants participating in classes but not using the EdReady program in order to better understand this relationship between in-class EdReady use and computer and math self-efficacy.

The p-value of 0.75 for the negative relationship between computer self-efficacy and number of EdReady classes indicates something unreliable about the data. It could be that attending EdReady classes lowered student computer self-efficacy on average, however an exploration of EdReady and post-survey data collection issues is warranted here.

It may be that EdReady really was not the best program for increasing students' computer self-efficacy. However, it is likely that the post-survey data is not a true representation of participant computer and math self-efficacy after the given number of EdReady classes. EdReady classes were intended to run from the end of January to the end of April but were stopped at the beginning of March. Additionally, post-surveys were not administered until June, three months after in-person classes had ended and the Covid-19 pandemic had begun having widespread effects throughout the U.S. Post-surveys were administered solely online, in contrast to the paper pre-surveys. Thus, post-survey responses only included participants with access to a smartphone, tablet, or computer, as well as the skills needed to complete a survey using that technology. It is possible that post-surveys are a better measurement of participants' computer and math self-efficacy as they related to the Covid-19 lockdown and distance learning, versus the effects of a truncated period of in-person computer-based classes. With respect to computer self-efficacy in particular, participants' responses to the computer self-efficacy post-surveys may have been particularly skewed by the sharp increase in demands on their digital skills because of the pandemic, including both the distance learning they were trying to do, as well as with respect to other areas of their lives.

Despite these data collection issues, it is still interesting that pre-survey computer self-efficacy scores had a negative and statistically significant relationship to change in computer self-efficacy. This indicates that participants with lower starting computer self-efficacy were more likely to perceive a positive change in their computer self-efficacy as compared to participants with higher starting self-efficacy. Similarly, pre-survey math self-efficacy scores had a negative and statistically significant relationship with changes in math self-efficacy. One interpretation of this is that even a small amount of class time can have a positive effect on self-efficacy of those with very low self-efficacy to start with. However, this does not explain why students with relatively high self-efficacy would be more likely to experience a decrease in computer and math self-efficacy. It could be that initially, individuals with high computer self-efficacy that does not match their actual skills with using the computer experience a period of readjustment of their self-efficacy when they begin working with the computer in the classroom. It would be worthwhile to extend the period of in-class EdReady use to see if and how computer self-efficacy changes over time. Would students with high initial computer self-efficacy see their self-efficacy restored after a drop-off in the beginning?

5.2.3 Math Performance and EdReady Use

The third research question is difficult to address due to there only being three math post-test scores for participants who took surveys and participated in the EdReady classes. The three changes in math TABE score do reflect the pattern of having no discernible pattern found in the rest of the results. The participant with the lowest number of EdReady classes started with a high math score and decreased only slightly. The student who attended a moderate number of EdReady classes had a lower math score and increased significantly in their post-test. The student who attended the highest number of EdReady classes decreased moderately on their math performance. See Figure 4.15.

5.3 Conclusion and Directions for Future Research

Computer and math self-efficacy were not found to significantly impact math performance in this study. This is indicative of the challenge of collecting data with an ABE program setting, and complexity of the relationship between self-efficacy and academic performance. Further, though it is known that domain-specific self-efficacy is a strong predictor of performance in that domain, this study was concerned with how one domain impacts another – how computer self-efficacy impacts math performance (on computer-based tests). In another study of a similar population, Southerlin (2016) found computer self-efficacy to be significantly related only to RLA and Science performance for first-time GED test-takers, and not Math or Social Studies. Future studies should administer surveys to first-time takers of the TABE at the time of the test to gain a broader sample and closer relationship between the surveys and the test. The surveys used should include items on other related concepts, such as anxiety and self-concept, which are known to impact performance as well.

Guided, in-class use of an online educational program was not found to significantly impact computer self-efficacy but had a positive yet insignificant ($p = .06$) impact on math self-efficacy. A future study should include a longer period of in-class guided use of online educational programs across several instructors' classes or across several programs, so that EdReady use can be compared with non-EdReady use, and so that short-term and long-term changes in self-efficacy can be captured.

Because ABE students are increasingly required to use computers to take standardized tests, because domain-specific self-efficacy is known to be a strong predictor of academic performance, and because ABE programs need to best determine how to incorporate computers into the classroom, this study sought to better understand that relationship between computer and math self-efficacy and math performance. Though overall the results were inconclusive, they point to future investigations into how closely computer and math self-efficacy is tied to math scores and how computer and math self-efficacy are affected by in-class computer use.

The lack of peer-reviewed research focusing on adult basic and secondary education is reflective of the relatively small proportion it occupies in the field of education, and the challenge of collecting data from these programs. However, millions of adults in the U.S. stand to benefit from these programs, and the programs themselves stand to benefit from being able to use evidence-based strategies to improve the lives of those they serve.

APPENDICES

APPENDIX 1. Computer User Self-Efficacy Scale

Computer User Self-Efficacy Survey

First Name:______________ Last Name: ________________ Date of Birth (MM/DD/YYYY):_________________________

The purpose of this questionnaire is to examine attitudes toward the use of computers. The questionnaire is divided into two parts. In Part 1 you are asked to provide some basic background information about yourself and your experience of computers, if any. Part 2 asks you to indicate the extent to which you, personally, agree or disagree with the statements provided.

Part 1:

Your age __________________________________

Experience with computers (check one): ☐ None ☐ Very limited ☐ Some experience ☐ Quite a lot ☐ Extensive	Please check all of the computer programs you have used (if any): ☐ Word-processing ☐ Spreadsheets ☐ Databases ☐ Presentation software (e.g., PowerPoint) ☐ Internet browser (e.g., Internet Explorer, Firefox, Chrome) ☐ Other (specify)__________________________
Do you own a computer or tablet? ☐ Yes ☐ No	Have you ever attended a computer training course? ☐ Yes ☐ No

Part 2:
<u>Directions</u>: On the next page you will find a number of statements concerning how you might feel about computers. Circle the number that most closely represents how much you agree or disagree with the statement. A '1' means that your strongly disagree with the statement. A '6' means that you strongly agree with the statement. There are no correct responses; it is your own views that are important. Please respond to every statement.

		Strongly Disagree					Strongly Agree
1	Most difficulties I encounter when using computers, I can usually deal with.	1	2	3	4	5	6
2	I find working with computers very easy.	1	2	3	4	5	6
3	I am very unsure of my abilities to use computers.	1	2	3	4	5	6
4	I seem to have difficulties with most of the programs I have tried to use.	1	2	3	4	5	6
5	Computers frighten me.	1	2	3	4	5	6
6	I enjoy working with computers.	1	2	3	4	5	6
7	I find that computers get in the way of learning.	1	2	3	4	5	6
8	Computer programs don't cause many problems for me.	1	2	3	4	5	6
9	Computers make me much more productive.	1	2	3	4	5	6
10	I often have difficulties when trying to learn how to use a new computer program.	1	2	3	4	5	6
11	Most of the computer programs I have had experience with have been easy to use.	1	2	3	4	5	6
12	I am very confident in my abilities to make use of computers.	1	2	3	4	5	6
13	I find it difficult to get computers to do what I want them to.	1	2	3	4	5	6
14	At times, I find working with computers very confusing.	1	2	3	4	5	6
15	I would rather that we did not have to learn how to use computers.	1	2	3	4	5	6
16	I usually find it easy to learn how to use a new computer program.	1	2	3	4	5	6
17	I seem to waste a lot of time struggling with computers.	1	2	3	4	5	6
18	Using computers makes learning more interesting.	1	2	3	4	5	6
19	I always seem to have problems when trying to use computers.	1	2	3	4	5	6
20	Some computer programs definitely make learning easier.	1	2	3	4	5	6
21	Computer jargon baffles me.	1	2	3	4	5	6
22	Computers are far too complicated for me.	1	2	3	4	5	6
23	Using computers is something I rarely enjoy.	1	2	3	4	5	6
24	Computers are good aids to learning.	1	2	3	4	5	6
25	Sometimes, when using a computer, things seem to happen and I don't know why.	1	2	3	4	5	6
26	As far as computers go, I don't consider myself to be very competent.	1	2	3	4	5	6
27	Computers help save me a lot of time.	1	2	3	4	5	6
28	I find working with computers very frustrating.	1	2	3	4	5	6
29	I consider myself to be a skilled computer user.	1	2	3	4	5	6
30	When using computers, I worry that I might press the wrong button and damage it.	1	2	3	4	5	6

APPENDIX 2. Middle School Mathematics Self-Efficacy Scale

Math Self-Efficacy Survey

First Name:________________ Last Name: __________________ Date of Birth (MM/DD/YYYY):_____________

<u>Directions</u>: Below are a number of statements concerning how you might feel about math. Circle the number that most closely represents how you feel about the statement. A '1' means that you think the statement is definitely false. A '6' means that you think the statement is definitely true. There are no correct responses; it is your own views that are important. Please respond to every statement.

		Definitely False					*Definitely True*
1	I make excellent grades on math tests.	1	2	3	4	5	6
2	I have always been successful with math.	1	2	3	4	5	6
3	Even when I study very hard, I do poorly in math.	1	2	3	4	5	6
4	I got a good score in math on my last test.	1	2	3	4	5	6
5	I do well on math assignments.	1	2	3	4	5	6
6	I do well on even the most difficult math assignments.	1	2	3	4	5	6
7	Seeing other people do well in math pushes me to do better.	1	2	3	4	5	6
8	When I see how my math teacher solves a problem, I can picture myself solving the problem in the same way.	1	2	3	4	5	6
9	Seeing other people do better than me in math pushes me to do better.	1	2	3	4	5	6
10	When I see how another student solves a math problem, I can see myself solving the problem in the same way.	1	2	3	4	5	6
11	I imagine myself working through challenging math problems successfully.	1	2	3	4	5	6
12	I compete with myself in math.	1	2	3	4	5	6
13	My math teachers have told that I am good at learning math.	1	2	3	4	5	6
14	People have told me that I have a talent for math.	1	2	3	4	5	6
15	People in my family have told me what a good math student I am.	1	2	3	4	5	6
16	I have been praised for my ability in math.	1	2	3	4	5	6
17	Other students have told me that I'm good at learning math.	1	2	3	4	5	6
18	My classmates like to work with me in math because they think I'm good at it.	1	2	3	4	5	6
19	Just being in math class makes feel stressed and nervous.	1	2	3	4	5	6
20	Doing math work takes all of my energy.	1	2	3	4	5	6
21	I start to feel stressed-out as soon as I begin my math work.	1	2	3	4	5	6
22	My mind goes blank and I am unable to think clearly when doing math work.	1	2	3	4	5	6
23	I get depressed when I think about learning math.	1	2	3	4	5	6
24	My whole body becomes tense when I have to do math.	1	2	3	4	5	6

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